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MODELING OF MULTI-FACTORY DEPENDENCES IN COMPLEX CONTROL SYSTEMS BY SUGENO FUZZY KNOWLEDGE BASE

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Annotation. The creation of intelligent control systems based on soft computing for complex real-time systems is considered. Usually, the control of many objects and technological processes is performed by a human operator based on instructions and personal experience. Due to the uncertainty and incompleteness of information about the parameters of the object, the impossibility of their direct measurement and the natural diversity of the environment, the use of classical mathematical methods for the automation of control is impossible. Adaptive methods are used to solve the management problem under conditions of uncertainty. The most effective is the implementation of fuzzy control based on production rules, which does not require knowledge of the object model. The concept of fuzzy control is widely used because of its ability to operate according to conditions. The object is evaluated using fuzzy rules from the knowledge base that create a fuzzy decision domain.

The stage of structural identification of the system when modeling an unknown dependency by Sugeno's fuzzy knowledge base is presented, which allows implementing a control algorithm based on a neural network.

To take into account the maximum number of influencing factors, the hierarchical structure of the fuzzy control system is applied. Granulation by certain properties of the object and the environment at the level of input variables allows to reduce the dimensionality of the data vector and the number of rules of the knowledge base, making it possible to build fuzzy control systems with an unlimited number of inputs. According to this model, the decision-making process is divided into two levels. The first level reduces the amount of information to define the situations to be processed in the second level by the Sugeno knowledge base. A preliminary fuzzy model of control of complex dynamic objects with incomplete determination is built.

Keywords: fuzzy control sysrem, membership function, multivariate dependence, production rules, logical derivation, hierarchical structure, Sugeno knowledge base, Mandany algorithm.

Introduction

Performing control as a complex intellectual process in conditions of incomplete certainty, the human operator influences the object based on his own experience. A necessary condition for decision-making is taking into account various factors of the object's state and environment and high speed of decision-making in real-time conditions. The operator must assess the dynamics of changes in the object parameters, determine the strength and duration of the impact and the expected control result.

In the context of the intellectualization of management processes, in particular complex dynamic objects in real time, the introduction of computer-integrated tools that have the nature of functioning, close to the mental activity of a person, is relevant.

Automation usually requires knowledge of the process model, on the basis of which the corresponding control is performed. When the exact mathematical model is complex or when an analytical model of the object based on traditional mathematical tools cannot be built, the most effective is to apply soft computing.

Nowadays, fuzzy logic is considered as a standard method of modeling and designing. The goal of fuzzy logic is to eliminate complex mathematical relationships in favor of empirical experience. Therefore, its application for managing complex technological processes does not require knowledge of the model.

There are many opportunities to combine artificial intelligence and soft computing technologies to obtain hybrid algorithms for solving nonlinear problems that use uncertain and imprecise data and generate approximate solutions that are not inferior to the quality of operator control. At the same time, hybrid tools require a relatively short time to develop and are reliable [1]. Application of neural network adaptation for systems of high complexity and low determinism gives the best results.

Purpose

To build a fuzzy neural network model for controlling complex dynamic objects, which implements unknown mapping $y^{(k)} = f(x_1^{(k)}, x_2^{(k)}, ..., x_n^{(k)})$, using the tools of soft computing technology based on fuzzy systems.

Analysis of research and publications

Conventional fuzzy and neuro-fuzzy systems have dimensionality limitations. The main problem faced is the exponential increase in the number of rules as the number of variables increases, which increases the overall complexity of the system and affects performance. This limits the use of fuzzy systems for solving complex problems and real applications with large data dimensions.

Over the last decade, there has been a lot of effort to take into account the maximum number of parameters when constructing fuzzy systems. The hierarchical structure has become an acceptable solution to overcome the limitations of conventional fuzzy and neuro-fuzzy systems.

The integrated parameter model is proposed in [2]. A special structure with a hierarchical fuzzy model is applied to avoid the curse of dimensionality. The rules are grouped into modules, each of them calculates a partial solution, which is used in subsequent modules to calculate the final conclusion of the system. There are 4 hierarchical levels in the architecture: input (level 3), mixed (level 2), compatible (level 1) and integrated (level 0).

A complex management and control system with unstable characteristics and many disturbances is considered in [3]. A hierarchical fuzzy logic controller (HFLC) method is proposed. It consists of a number of low-dimensional fuzzy systems in a hierarchical form. The first level gives an approximate result, which is modified by a set of rules of the second level and repeated at the next levels of the hierarchy. The number of rules is reduced to a linear function of the number of inputs.

The authors [4] offer a methodology that allows you to reduce complexity while maintaining the required accuracy when tracking objects. Several dynamic fuzzy sets are constructed according to the properties distinguishing the tracked object. The properties used as descriptors are chosen in accordance with the specifics of the task to be solved. A fuzzy set is constructed to model each of the selected properties. Kinematic properties such as object velocity, acceleration, and other motion patterns undergo a similar process. Thus, the mechanism of logical derivation allows modeling the system to achieve a balance between information about kinematic and other important properties of objects and the required accuracy.

Work [5] presents an algorithm for a hierarchical system in the context of both type 1 and type 2 fuzzy inference systems. A hierarchical fuzzy tree structure is described at multiple levels and multiple systems at each level. The output of these fuzzy systems is used as input for the next sequential layer with input data.

The authors [6] use a hierarchical classification of state parameters, according to which a conclusion tree is built. It defines a system of nested statements-knowledge of a smaller dimension. The presentation of expert knowledge by levels is determined by the natural hierarchy of diagnostic objects and the need to take into account additional state parameters as knowledge about the object is accumulated.

A modified model of hierarchical fuzzy logical derivation with local submodels of two types - fuzzy and hybrid fuzzy-probabilistic is proposed in [7].

The author [8] considers the problem of correct docking of different types of elements in the construction of hierarchical fuzzy knowledge bases. The main methods of transferring the results of intermediate logical deductions in the hierarchical knowledge base are defined.

The use of neuro-fuzzy models in the modeling and control of complex systems requires the development of a general topology of fuzzy neuron models, learning algorithms and approximation theory [1].

Construction of the model

There are a number of specific requirements for modern management and control tools, such as:

– the need to take into account the diversity of situations, objects and operating conditions;

– the need to ensure operational data processing with the determination of state indicators and object control signal;

– compatibility with a common external database.

To the greatest extent, these requirements are met by the class of intelligent control and management tools using soft computing technology. Elements of fuzzy set theory, rules of implication, and fuzzy reasoning form a system of fuzzy inference. It consists of:

– a database containing a description of membership functions;

– a set of unclear rules;

– the mechanism of derivation and aggregation formed by the rules of implication.

The conceptual model of the system is built taking into account the implementation of all stages of decision-making based on the fuzzy inference algorithm. At the general level, the fuzzy control system can be distinguished: a control object, sensors of input variables, and a fuzzy reasoning system. However, there is no standard methodology for designing and calculating fuzzy systems.

The basic organization of the fuzzy control system, the influence of the environment, information connections and mutual connection of the main logical nodes and the control object is described by the module architecture shown in Fig. 1. The determination of the control signal is carried out by implementing the procedure of transition from the definition of the membership function to the numerical value of the control signal transmitted to the executive control mechanism.

A fuzzy control system operates in some environment that can influence the object. When considering a dynamic object without a source of energy, when the movement occurs under the influence of inertial forces, the environment and the state of the path have the main importance. This environment determines the circumstances of development and exploitation of this system. The environment may also contain other systems that interact with the system both directly and indirectly in other ways.

In the case of technical implementation, the input and output signals are measured numerical values, which make it possible to unambiguously correlate the input values of the variables with the corresponding output values of the control signal. Based on the principle of the unity of the object with the environment, technical parameters are interpreted as vague values in the interval of optimal (or permissible) functioning. At the same time, the limits of variation are movable and depend on the functional state of the object, wear out of technical means and differ in each specific case. Dependencies between parameters may be implicit, so the system operating with such parameters should allow for taking into account inaccuracies and partial uncertainties in the description of cause-and-effect relationships. In the unique operating conditions of complex systems, statistical methods are unacceptable, since it is not possible to collect statistics on the options for solving the problem of managing a certain object due to an infinite set of combinations of object parameters and the environment.

The problem of identification is reduced to the construction of a parametric control model so that the invented control signal coincides with the given reference signal within the limits of the permissible error $|\hat{y} - y| \le \varepsilon$. The determination takes into account qualitative interpretations of the state of the environment and the impossibility of applying such calculation methods as building an analytical model of regression

$$y^{(m)} = f(x_1^{(m)}, x_2^{(m)}, ..., x_N^{(m)})$$

where $X^{(m)} = x_1^{(m)}, x_2^{(m)}, ..., x_N^{(m)}$ – specific parameter values $(x_1, x_2, ..., x_N)$ for m-input data set;

$y^{(m)}$ – specific value of the output signal for m-data set.

It is convenient to build a hybrid neuro-fuzzy control model for determining the state of complex objects [9] based on the Takagi-Sugeno-Kang (TSK) fuzzy logic inference system. These fuzzy models are universal approximators.

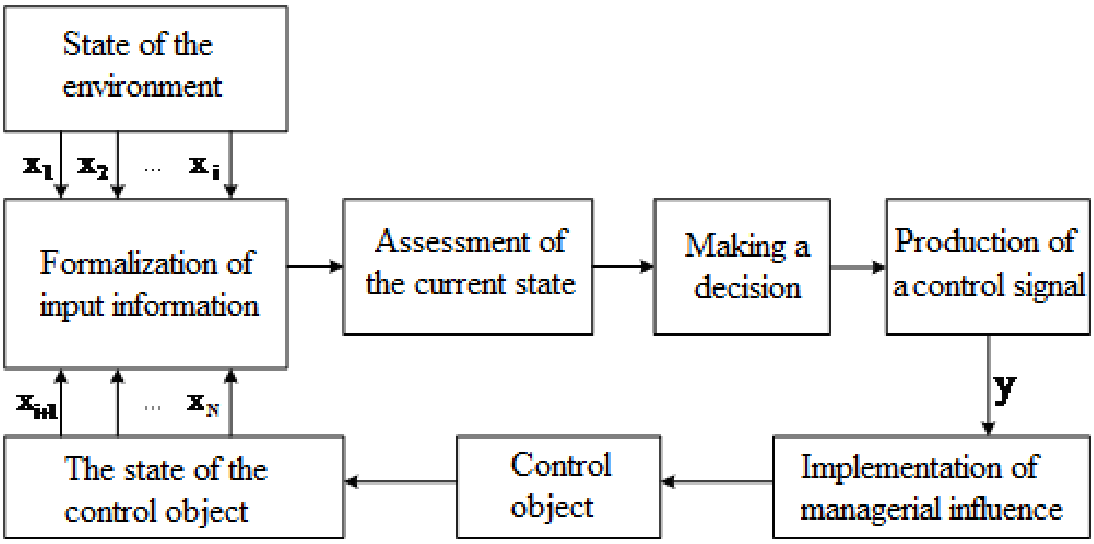

Fig. 1. Logical architecture of the fuzzy control module.

Almost all nonlinear dynamic systems can be represented by Takagi-Sugeno fuzzy models with a high degree of accuracy [10]. The advantage of such a fuzzy structure is a very simple calculation of the output value [11]. There is a possibility of retraining with adjustment of parameters using a fuzzy neural network after the system is built on the available data. However, there are no standard methods of transforming knowledge or experience into a rule base and database of a fuzzy inference system [1].

Assume that the parameters read from the sensors are distinct inputs for the linguistic variables. Determining the number of terms does not have any theoretical approach, the heuristic search method works. Let's take the number of terms of a separate term-set from 3 to n depending on the rate of change of the parameter. Having specified on the domain X a fuzzy partition $\tilde{A}$ with parameter $\alpha (0 \le \alpha \le 1)$ as a family of fuzzy sets $\tilde{A} = \{A_1, A_2, ..., A_n\}$, where $\forall x_i \in X$ for $\exists i \in \{1,,2,...N\}$, the membership function of the influencing factor will be determined by $\mu_{A_i}(x) \ge \alpha$ (Fig. 1). The preliminary placement of the membership functions is arbitrary, taking into account further customization.

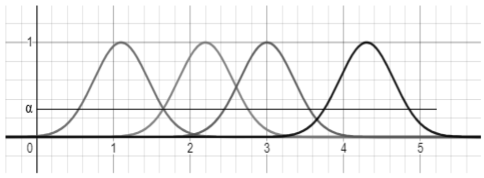

Fig. 2. Fuzzy division of the input variable definition area.

One of the main ways of assigning membership functions of continuous fuzzy sets is to use some given model of the function and adjust its parameters manually or automatically. Assuming the initial equivalence of the action of various factors and their variations, we choose a membership function of the class π in the form of the most widely used Gaussian curve, described by the formula:

$$f(x) = \exp\left(-\frac{(x-m)^2}{\sigma^2}\right).$$

A symmetrical Gaussian curve is characterized by the location of the mode and the deviation of the distribution, which are subject to adjustment, since the equivalence of the action of various factors in real systems is not fulfilled. Due to the initial parametric and quantitative uncertainty, and heterogeneity of the dynamic characteristics of objects, membership functions within a

certain control system are adjusted during training. Deviations of the distribution due to the influence of environmental factors and the state of the object are revealed in a plateau-like or slanted shape of the curve of the membership function. However, these deviations from the symmetric shape have a private local character that can be detected during training for a specific control object according to the application.

Performing the procedure of identification of input parameters helps to find optimal parameters of membership functions that minimize the quality indicator. Nonlinear forms of membership functions are constructed using a neural network based on convergence. This makes the neuro-fuzzy control system suitable for solving specific tasks of a certain area with a given accuracy.

Sugeno fuzzy knowledge base

A set of facts and rules of logical derivation in a certain subject area form the knowledge base of a fuzzy control system that determines the relationship between the inputs and outputs of the object. Since fuzzy control is multi-valued, it allows modeling both numerical dependencies and the empirical experience of a human operator, expressed in the form of a base of linguistic rules, which are formulated in terms of control influences on a defined set of input variables. The application of the Sugeno knowledge base with multidimensional fuzzy inference has several advantages [12]. This is a more compact size of the rule base and lower computational complexity by reducing the number of implications and simplifying reasoning.

Denoting the influence factors with a N-dimensional vector $X=(x_1,x_2,...x_N)$, and the necessary control influence with $Y=(y_1,y_2,...,y_k)$, the control model will represent a classification - assigning an object with certain parameters to one of the classes. This is a mapping $X_i \to y_j$, $j=1,2,...,q$, which can be described by Sugeno fuzzy knowledge base in the form of k fuzzy rules $R^{(k)}$, as a generalized model of the representation of knowledge about the subject area:

$$R^{(k)}: IF\ (x_1\ IS\ A_1^k\ AND ... x_n\ IS\ A_n^k)$$
$$THEN\ y=f^{(k)}(x_1,...,x_n),\ i=1,...n.$$

The conditions of the rules $(IF\ x_i\ IS\ A_i^k)$ are implemented by the fuzzy set membership function $\mu_A(x_i)\in[0;1]$ for each of input variable x_i. The conclusions of the rules are an arbitrary real function of the input variables [12], usually a linear function represented by a polynomial with parameters:

$$f^k(x_1,...,x_n)=c_0^k+c_1^k x_1+...+c_m^k x_m,$$
$$j=1,...m.$$

The function $f^{(k)}$ is a direct mapping of the input space X with the input values $x_1,x_2,...x_N$ into the output space Y with the output value y_j. Ensuring a continuous smooth resulting transition between output functions under the condition that membership functions of fuzzy sets in rule conditions overlap is an advantage of the Sugeno knowledge base.

Fuzzy logical deduction

There are various variants of modifying fuzzy inference [13], where the algorithms differ mainly in the logical operations applied to fuzzy sets.

When implementing fuzzy control, for each specific value of the input vector of variables $\overline{X}=(\overline{x}_1,\overline{x}_2,...,\overline{x}_N)\in X$, which is a vector of the current state of the object, the values of the membership functions of the prerequisites $\mu_A^{(k)}(X)$ are calculated, which determine the weight w_k of each rule.

Assuming that the sought fuzzy set for the rule $R^{(k)}$ is defined as a N-dimensional fuzzy conjunction $A=A_1\cap A_2\cap...\cap A_N$ with a membership function

$$\mu_{\overline{A}}(\overline{X})=T(\mu_{A_1}(\overline{x}_1),\mu_{A_2}(\overline{x}_2),...,\mu_{A_N}(\overline{x}_N)).$$

It will be determined by the T-norm corresponding to the logical operation "AND" over the values of membership x_i to fuzzy terms. As a rule, the logical operation min-

conjunction is used:

$$\mu_{\bar{A}}^{(i)}(\bar{X}) = \min(\mu_{A_1}(\bar{x}_1), \mu_{A_2}(\bar{x}_2), ..., \mu_{A_N}(\bar{x}_N)).$$

Having obtained the value of the membership function for all k rules of the knowledge base, the k-dimensional vector of the weight of the rules $\overline{W}$ for the vector of input variables $\bar{X} = (\bar{x}_1, \bar{x}_2, ..., \bar{x}_N)$ is the following:

$$\overline{W} = (\mu_{\bar{A}}^{(1)}(\bar{X}), \mu_{\bar{A}}^{(2)}(\bar{X}), ..., \mu_{\bar{A}}^{(k)}(\bar{X})).$$

Individual output values for each of the rules are calculated by a linear equation

$$y_j(X_i) = c_0^k + \sum_{i=1}^{N} c_N^k x_N ,$$

where coefficients c_i are weights that are adjusted during the learning process of the neural network.

Since each rule has its own clear output, when applying k fuzzy rules, the output control signal will be determined by the normalized weighted sum of individual values.

$$\hat{y} = \frac{\sum_{j=1}^{k} w_j \cdot y_j}{\sum_{j=1}^{k} w_j} = \frac{\sum_{j=1}^{k} w_j \cdot \left(c_0^k + \sum_{i=1}^{N} c_N^k x_N \right)}{\sum_{j=1}^{k} w_j}$$

Avoiding the time-consuming defuzzification process is an advantage of applying the Sugeno knowledge base to the control module.

In accordance with the algorithm, when forming a control influence based on a certain set of rules, a connection is established between the current state of the dynamic system and the need for control. For this, the linear function in the conclusion must be adapted. Finding the optimal parameters $c_i^{(k)}$ for a certain subject area is reduced to nonlinear programming, which minimizes the quality $|\hat{y} - y| \le \varepsilon$.

Consequence parameters that give the smallest loss function in the classical algorithm [12] are searched by the method of least squares for given variables.

It should be noted that the Takagi-Sugeno model has difficulties with multi-parameter estimation due to the need to assign weight to each of the inputs and fuzzy rules, while it works well with linear methods, guaranteeing the continuity of the output surface [1].

Hierarchical structure

Building a model with many parameters of the control object and environmental factors causes an exponential increase in the dimension of the fuzzy system and a decrease in the speed of formation of the control influence to the object due to a large volume of calculations. The dimensionality of the feature space should be as small as possible to simplify the control process and increase the statistical stability of the results. However, reducing the number of input variables leads to an increase in the control error. Therefore, the formation of the space of input variables is a compromise between complexity and accuracy. The use of hierarchical fuzzy logic derivation when modeling multidimensional dependence allows to overcome the "curse of dimensionality". With this construction, the control model consists of fuzzy models of smaller dimensions. The lowest level of the hierarchical structure has access to real input parameters, and the outputs of the models of the previous level become the inputs of the models of the next level [9].

To calculate the values of the control signal, it is necessary to determine the elements of the hierarchical fuzzy system and the relationship between them, based on classical fuzzy logical operations. The main goal is to synthesize sequential algorithms of local modules and build a procedure for combining the output signals of individual modules to obtain the optimal output signal of a fuzzy control system, which is not inferior in accuracy to a human operator.

By applying hierarchical fuzzy logical inference to the elements of evaluating the current state of the control object, private input influencing factors $a_i \in X$ are grouped into generalized criteria $b_j \in B$ [14]. Then the

fuzzy set $B \subseteq X = f(A)$ enters the input of the decision making block.

The task is to determine the mapping $f_i:(a_1,a_2,...,a_n) \to b$, $f_j:(b_1,b_2,...,b_k) \to c$ using the base of rules, where c is the output value of the fuzzy system – the control signal.

Dynamic object parameters and environment properties are grouped as follows:

– movement parameters;
– path parameters;
– parameters of the surrounding environment, etc.

Input signals are sent to an element that implements a non-linear function, which can have any form. Figure 3 shows an example of a two-level fuzzy inference hierarchical structure that models dependency $y = f(a_1, a_2, a_3, ..., a_n)$ using k links that describe dependencies:

$$b_1 = f_1(a_1, a_2, a_3);$$
$$b_2 = f_2(a_4, a_5, a_6);$$
$$\ldots;$$
$$b_k = f_k(a_{k(n-2)}, a_{k(n-1)}, a_{kn}).$$

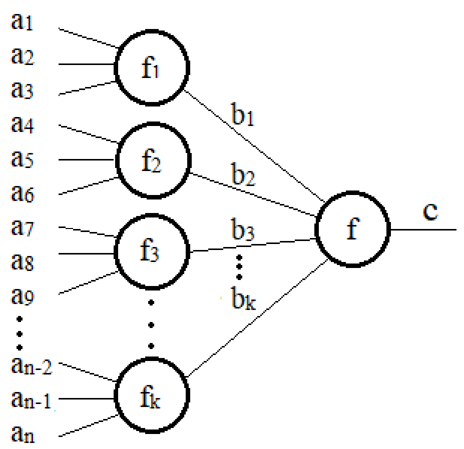

Fig. 3 The structure of hierarchical fuzzy logical inference.

The advantage of the hierarchical structure is a significant reduction in the fuzzy rules of the knowledge base for an adequate description of the multidimensional dependence "input-output" and an increase in the speed of calculations in real-time systems.

Reducing the dimensionality of input data

Qualitative interpretation of parameters as linguistic variables is conveniently carried out on the basis of the Mamdani method [15], which is a well-known derivation system and has a number of advantages: a more intuitive nature of fuzzy reasoning when working with uncertainty [11], a well-interpreted base rule base that look like:

$$R^{(q)}: IF\ x_1\ is\ A_1^{(q)}\ AND\ x_2\ is\ A_2^{(q)}\ AND \ldots x_n\ is\ A_n^{(q)}$$
$$THEN\ b_j\ IS\ B_j^{(q)},$$

where k is the number of rules;
a_i – input variables of the control system;
b_j – output variables of the intermediate hierarchical level;
B_j – continuous membership functions of generalized integral factors;

Numerical and linguistic signals $a_i = x_i$ are received at the input of the fuzzy control module, which is the lower level of the hierarchical system, as a vector of the current state of the object. Applying fuzzy logical derivation according to Mamdani's algorithm [13], we use fuzzification of current data on a non-singleton function.

For the Mamdani-Zadeh algorithm, degrees of truth of all components of the conditions for the current input vector $\overline{X} = (\overline{a}_1, \overline{a}_2, ..., \overline{a}_N)$ are determined for each rule R_i of the fuzzy inference system. When applying the T-norm on the right side of the rules, which is implemented by the logical operator [15] or an arithmetic product, the membership is

$$\mu_A(a) = \min(\mu_{A_1}(a_1), \mu_{A_2}(a_2), ..., \mu_{A_N}(a_N)),$$
$$\mu_A(a) = \prod_{i=1}^{N} \mu_A(a_i)$$

Determining the activation level of the rule and the value of the membership function for the entire implication $A \to B$ using the logical or arithmetic product operator is written as

$$\mu_{A\to B}(a,b)=\mu_A(a)\wedge\mu_B(b)=\min(\mu_A(a),\mu_B(b))$$

By accumulating the conclusions of fuzzy rules, the found fuzzy subsets are combined by a logical sum operation $B=B_1\cup B_2\cup\ldots\cup B_k$ with the membership function

$$\mu_B(b)=\max(\mu_{B_1}(b_1),\mu_{B_2}(b_2)\ldots\mu_{B_K}(b_k))$$

Then the final expression of the mathematical description of the intermediate hierarchical level of the fuzzy module, which performs dimensionality reduction of the input data according to the Mamdani algorithm, will have the form:

$$\mu_{B_j}(b_j)=\max\Big(\min\Big(\mu_B(b),\ \min\Big(\mu_{A_1}(a_1)\ldots\mu_{A_N}(a_N)\Big)\Big)\Big)$$

Given that the mapping $f_j:(b_1,b_2,\ldots,b_k)\to c$ will be implemented by the Sugeno knowledge base, it is necessary to match the output of the intermediate hierarchical level with the input of the next level. In [8], options for docking various types of elements in the construction of hierarchical fuzzy knowledge bases are considered. Accordingly, there are two options: with the defuzzification of the results of the intermediate hierarchical level and the transmission of fuzzy values in the form of fuzzy sets, which requires reconciliation.

The conclusions of the rules used in the Sugeno knowledge base are a clear function of the input variables, usually represented by a polynomial with parameters $f^{(k)}(x_1,\ldots,x_N)=c_0^k+c_1^k x_1+\ldots+c_N^k x_N$, so we will apply the variant with defuzzification of the results of the intermediate hierarchical level.

The experience of using this method of transferring intermediate results of logical derivation, as noted in [8], provides good tuning during parametric identification of a fuzzy model.

The defuzzification operation determines the precise point value of the output variables $\bar{b}_j$, which are the intermediate results that are fed to the input of the Sugeno model, at the current value of the input vector $\bar{X}=(\bar{a}_1,\bar{a}_2,\ldots,\bar{a}_n)$.

For the figure of the combined truncated set, reduction to real values can be performed by defuzzification using the mean center method:

$$\bar{b}=\frac{\sum\limits_{j=1}^{k}\mu_{B_j}(\bar{b}_j)\cdot\bar{b}_j}{\sum\limits_{j=1}^{k}\mu_{B_j}(\bar{b}_j)},$$

where $\bar{b}_j$ is the point at which the membership function takes the maximum value $\mu_{B_j}(\bar{b}_j)=max(\mu_B(b))$.

The results determined by Mamdani fuzzy classifier are used as input data of the Sugeno knowledge base in the procedure of predictive assessment of the functional state and control of the object.

Thus, the fuzzy output model allows describing the output signal of a multidimensional process as a nonlinear function of the input variables, the state of the environment, and the parameters of the fuzzy system.

The synthesis of the fuzzy control module, in addition to the selection of the membership functions of the term-sets of linguistic variables and the fuzzy derivation algorithm, involves the optimization of the main parameters of the control module (ranges of changes in linguistic variables, the form and parameters of the membership functions) by minimizing the selected quality criterion. To clarify the coefficients of the equations and the parameters of the membership functions of the left parts of the rules, it is necessary to present the TSK system in the form of a fuzzy neural network with subsequent training.

Training methods provide opportunities to adapt the intelligent control system to operating conditions. The selection of the initial variant of the placement of the membership functions and the establishment of fuzzy control rules involves the following search for the parameters of the equations and the best variant of the placement of the membership functions. The necessary operations of finding a control solution are formalized on the basis of the created fuzzy

Sugeno base.

Conclusions

The technology of soft computing is used to automate the control of complex objects under conditions of incomplete certainty. The stage of structural identification of the system when modeling an unknown dependency with Sugeno fuzzy knowledge base is presented. A preliminary fuzzy control model of complex dynamic objects is constructed. It requires research on the application of various logical operators in knowledge base modeling and inference algorithms to determine the best combination in a fuzzy control model.

Hierarchical fuzzy systems with parameter adaptation implemented by neural networks are the optimal choice for implementing control of complex dynamic objects with the ability to achieve appropriate control accuracy. Soft computing makes it possible to adjust to the required number of input variables, work in accordance with the state of the object, path, external influences, various operating conditions and provide good results.

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